Ph.D. Research Proposal

On

Analysis of Biomedical Signals using Wavelets

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INTRODUCTION

Wavelets:

A wavelet is a “small wave”, which has its energy concentrated in time. It gives a tool for the analysis of transient, non-stationary, or time-varying phenomena. It not only has an oscillating wavelike characteristic but also has the ability to allow simultaneous time and frequency analysis with a flexible mathematical foundation. Wavelets are the mathematical functions that cut up data into different frequency components and then study each component with a resolution matched according to its scale.
Wavelet analysis is similar to Fourier analysis in the sense that it breaks a signal down into its constituent parts for analysis. Whereas the Fourier transform breaks the signal into a series of sine waves of different frequencies, the wavelet transform breaks the signal into its "wavelets", scaled and shifted versions of the "mother wavelet". There are however some very distinct differences as is evident in Figure 1, which compares a sine wave to the Debauchies 5 wavelet. In comparison to the sine wave which is smooth and of infinite length, the wavelet is irregular in shape and compactly supported. It is these properties of being irregular in shape and compactly supported that make wavelets an ideal tool for analyzing signals of a non-stationary nature. Their irregular shape lends them to analyzing signals with discontinuity's or sharp changes, while their compactly supported nature enables temporal localization of signals features.

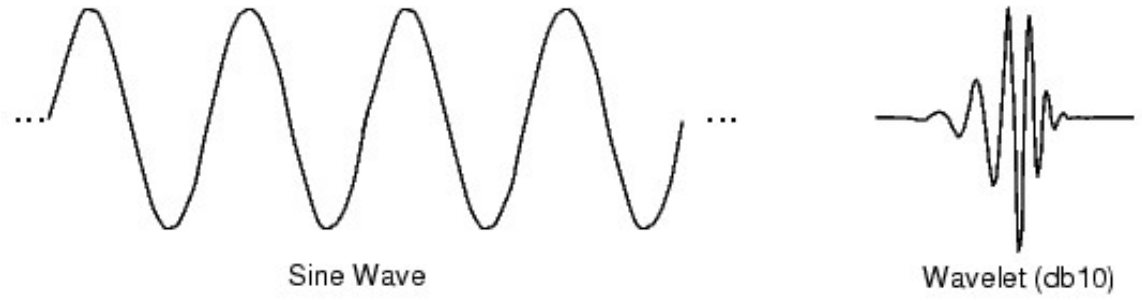


FIGURE 1 A COMPARISON OF THE SINE WAVE AND THE DAUBECHIES 10 WAVELET

When analyzing signals of a non-stationary nature, it is often beneficial to be able to acquire a correlation between the time and frequency domains of a signal. The Fourier transform, provides information about the frequency domain, however time localized information is essentially lost in the process. The problem with this is the inability to associate features in the frequency domain with their location in time, as an alteration in the frequency spectrum will result in changes throughout the time domain. In contrast to the Fourier transform, the wavelet transform allows exceptional localization in both the time domain via translations of the mother wavelet, and in the scale (frequency) domain via dilations. The translation and dilation operations applied to the mother wavelet are performed to calculate the wavelet coefficients, which represent the correlation between the wavelet and a localized section of the signal. The wavelet coefficients are calculated

for each wavelet segment, giving a time-scale function relating the wavelets correlation to the signal. This process of translation and dilation of the mother wavelet is depicted below in Figure 2.

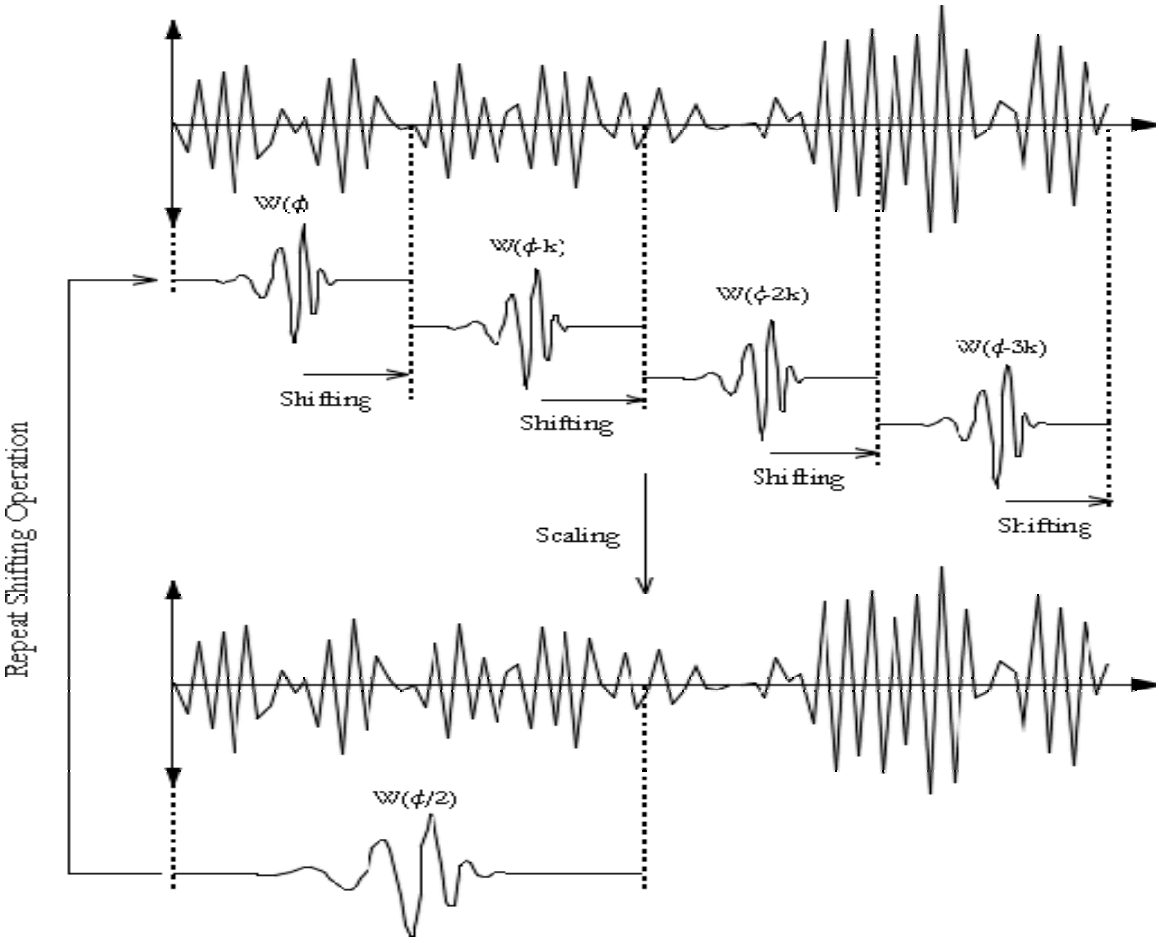


FIGURE 2: THE SCALING AND SHIFTING PROCESS OF THE DWT

The effect of this shifting and scaling process is to produce a time-scale representation, as depicted in Figure 3. As can be seen from a comparison with the STFT, which employs a windowed FFT of fixed time and frequency resolution, the wavelet transform offers superior temporal resolution of the high frequency components and scale (frequency) resolution of the low frequency components. This is often beneficial as it allows the low frequency components, which usually give a signal its main characteristics or identity, to be distinguished from one another in terms of their frequency content, while providing an excellent temporal resolution for the high frequency components which add the nuance's to the signals behavior.

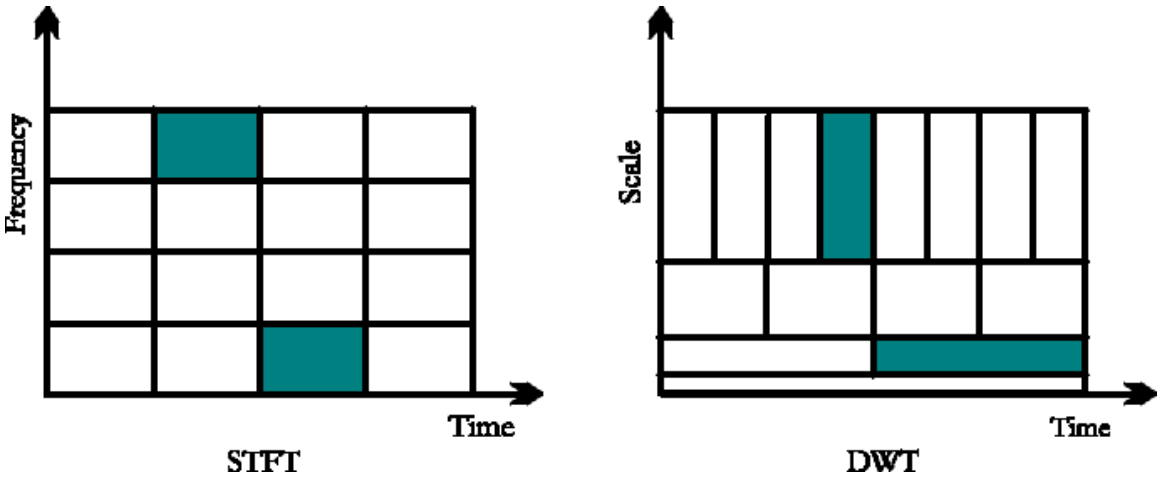


FIGURE 3: STFT AND DWT BREAKDOWN OF A SIGNAL

The dilation function of the discrete wavelet transform can be represented as a tree of low and high pass filters, with each step transforming the low pass filter as shown in Figure 4. The original signal is successively decomposed into components of lower resolution, while the high frequency components are not analyzed any further. The maximum number of dilations that can be performed is dependent on the input size of the data to be analyzed, with 2N data samples enabling the breakdown of the signal into N discrete levels using the discrete wavelet transform.

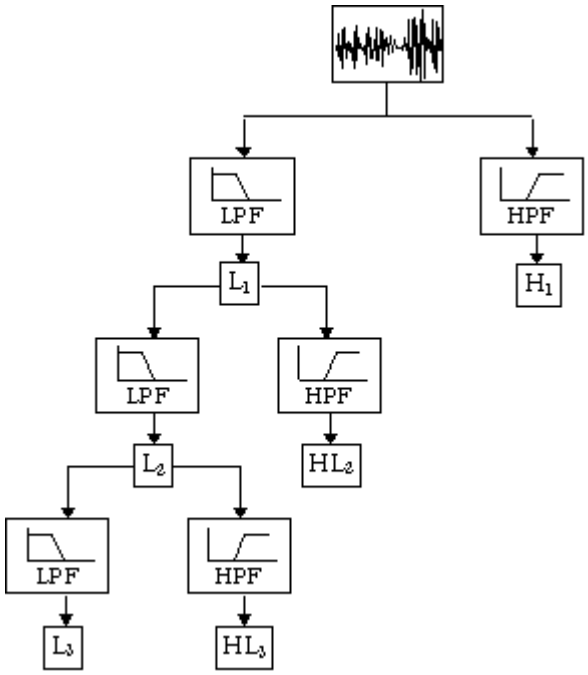


FIGURE 4: FILTER BANK REPRESENTATION OF THE DWT DILATIONS

The versatility and power of the DWT can be significantly increased by using its generalized form, wavelet packet analysis (DWPA). Unlike the DWT which only decomposes the low frequency components (approximations), DWPA utilizes both the

low frequency components (approximations), and the high frequency components (details). Figure 5 shows the wavelet decomposition tree.

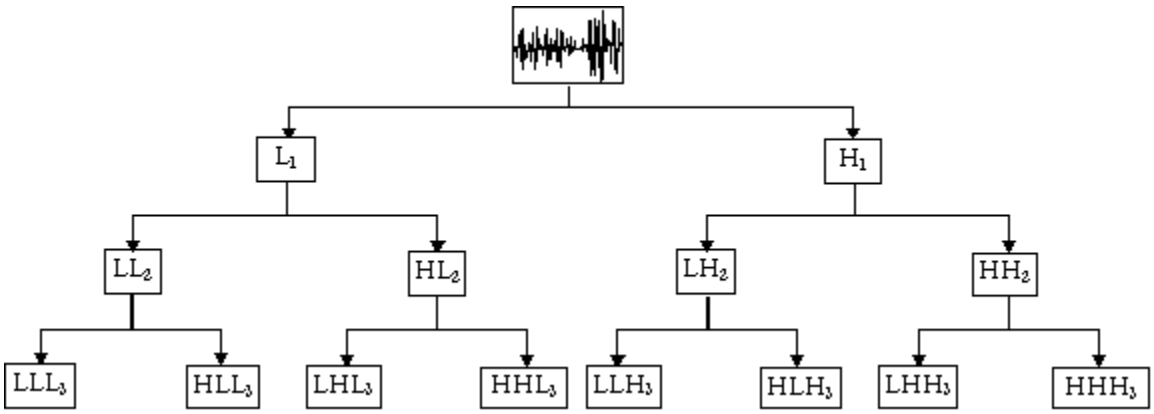


FIGURE 5: DWPA TREE DECOMPOSITION

DWPA allows the signal to be decomposed into any of 2N different signal encoding schemes. Choosing the optimum scheme for a particular signal is usually achieved by determining the best basis for the tree, normally through an entropy based criterion. [MISI96]. Wavelet packet analysis offers superior resolution and clarification of details about the signal.

The Continuous Wavelet Transform Equation

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^* \left(\frac{t-\tau}{s}\right) dt$$

The transformed signal is a function of two variables, **tau** and **s**, the **translation** and **scale** parameters, **psi(t)** is the transforming function, and it is called **the mother wavelet**.

LITERATURE SURVEY

Stephane G. Mallat (1989). Mallat studied the properties of the operator which approximates a signal at a given resolution. He showed that the difference of information between the approximation of a signal at the resolutions $2^{'+'}$ and 2^{j} can be extracted by decomposing this signal on a wavelet orthonormal basis of $L^{2}(R^{n})$. This decomposition defines an orthogonal multiresolution representation called a wavelet representation. It is computed with a pyramidal algorithm based on convolutions with quadrature mirror filters.

Metin Akay(1995). Akay compared various methods for biomedical signal processing only to conclude that wavelet transform is the best among all these methods. He gave the advantages and disadvantages of all the techniques used in the signal processing and proposed wavelet transform for biomedical signals as they are non-stationary in nature.

Michael Unser**(**1996**).** This paper emphasizes the statistical properties of the wavelet transform and discusses some recent examples of application in medicine and biology. The redundant forms of the transform (CWT and wavelet frames) are well suited for detection tasks (e.g., spikes in EEG, or micro-calcifications in mammograms). The CWT, in particular, can be interpreted as a pre-whitening multi-scale matched filter. Redundant wavelet decompositions are also very useful for the characterization of singularities as well as the time-frequency analysis of non-stationary signals. Some examples of applications in Phonocardiography, ECG and EEG are also discussed in the paper.

Metin Akay & Claudia Mello(1997). In this paper the general idea of the wavelet representation, in its continuous and discrete version, as well as in terms of a multi-resolution approximation has been discussed. In addition, the general expression for the Affin Class, and the relationship between the Affin and Cohen's Class are presented. Also, the Shift-Scale Invariant Class is defined. This class basically combines the properties of both classes. Finally, a recent development, namely, - the use of unitary transformations in both Cohen's and the Affine Classes, with the consequent generation of even more specific tools for signal analysis is discussed.

Jun Kong, Zheru Chi and Weixue Lu (1998). This paper presents a new ElectroCardioGram (ECG) compression method for applications in both ECG transmission and ECG data storing. The local modulus maxima of the wavelet transform of an ECG signal indicate the locations of sharp variation points in the signal that carry the most important information. Although a signal cannot be exactly reconstructed from the modulus maxima of its wavelet transform, we can obtain a close approximation of the original signal from these modulus maxima. By ignoring small modulus maxima and encoding only the locations and amplitudes of the remaining modulus maxima and the coarse scale signal, we can compress ECG signal significantly. Considering different energy levels at different scales, suitable thresholds are determined to remove unnecessary modulus maxima, such as those generated by noise and artifacts. With a high

compression ratio (CR) and a low percentage root-mean-square (PRD), our approach of ECG compression is comparable favorably with other methods tested.

Mateo Aboy, Cristina Cresp, James McNames(). This paper describes a biomedical signal processing (BSP) toolbox for the analysis of physiologic signals. The BSP toolbox is designed to enable researchers to conduct preliminary analysis of physiologic time series, such as the electrocardiogram (ECG), intracranial pressure (ICP), arterial blood pressure (ABP), and oxygen saturation (SpO2). The toolbox includes detection algorithms for the ECG and pressure waveforms, spectral analysis, nonlinear filtering, multi-signal analysis, and non-stationary signal visualization. The various sections discuss the functionality of this toolbox and provide examples of its application.

Jong Yong A. Foo(2006). In this paper it is shown that Photoplethysmography (PPG) can be used in time-related measurements such as heart rate (HR) and pulse transit time (PTT) estimations in the medical fields. The accuracy of these two parameters is heavily dependent on the minimal phase variability of the PPG signals. Moreover, motion artefact is a common phenomenon that can contaminate the PPG signals. This paper compares the capabilities of two signal processing techniques; digital adaptive filtering and discrete wavelet transformation, in restoring artefact-induced PPG signals during two regulated mild movements. HR comparison was evaluated against estimates attained from an electrocardiogram (ECG) while PTT evaluation was based on a reference PPG source free of artefacts. Comparison criteria was based on documented evidences that a HR difference of <10 beats per minute (bpm) and relative PTT changes of <15 ms can be considered as normal. The obtained results reveal that wavelet transformation is limited in restoring corrupted PPG signals for both HR and PTT measurements. It can also be observed its inherent algorithm can induce unwarranted phase variability that can compromise clinical interpretation of these two physiologic parameters.

Laurent Brechet, Marie-Françoise Lucas, Christian Doncarli, and Dario Farina (2007). They proposed a novel scheme for signal compression based on the discrete wavelet packet transform (DWPT) decompositon. The mother wavelet and the basis of wavelet packets were optimized and the wavelet coefficients were encoded with a modified version of the embedded zerotree algorithm. This signal dependant compression scheme was designed by a two-step process. The first (internal optimization) was the best basis selection that was performed for a given mother wavelet. For this purpose, three additive cost functions were applied and compared. The second (external optimization) was the selection of the mother wavelet based on the minimal distortion of the decoded signal given a fixed compression ratio. The mother wavelet was parameterized in the multiresolution analysis framework by the scaling filter, which is sufficient to define the entire decomposition in the orthogonal case. The method was tested on two sets of ten electromyographic (EMG) and ten electrocardiographic (ECG) signals that were compressed with compression ratios in the range of 50%–90%. For 90% compression ratio of EMG (ECG) signals, the percent residual difference after compression decreased from (mean SD) 48.6 9.9% (21.5 8.4%) with discrete wavelet transform (DWT) using the wavelet leading to poorest performance to 28.4 3.0% (6.7 1.9%) with DWPT, with optimal basis selection and wavelet optimization. In conclusion, best basis selection and

optimization of the mother wavelet through parameterization led to substantial improvement of performance in signal compression with respect to DWT and random selection of the mother wavelet. The method provides an adaptive approach for optimal signal representation for compression and can thus be applied to any type of biomedical signal.

Orlando Jos´e Ar´evalo Acosta and Matilde Santos Pe˜nas (2007). This contribution consists on the application of a hybrid technique of signals digital processing and artificial intelligence, to classify two kinds of biomedical spectra, normal brain and meningioma tumor. Each signal is processed to extract the relevant information within the range of interest. Then, a Haar 4 wavelet transform is applied to reduce the size of the spectrum without loosing its main features. This signal approximation is coded in a binary set which keeps the frequencies that could have representative amplitude peaks of each signal. The coding is input in a recursive Hamming neural network previously trained, which is able to classify it by comparing it with patterns. The results of the classification are shown for a group of signals that corresponds to human brain tissue. The advantages and disadvantages of the implemented method are discussed.

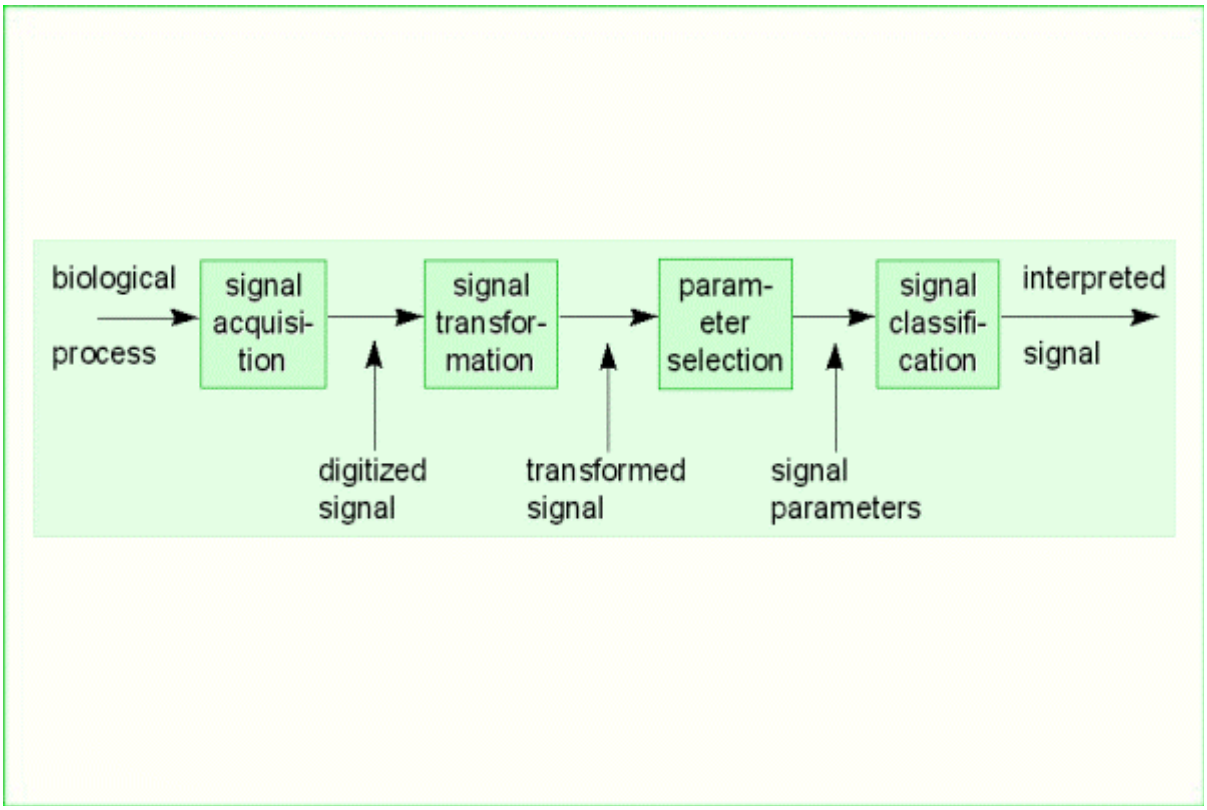
Ilker Bayram, Ivan W. Selesnick (2007). The author discusses the 2-band discrete wavelet transform (DWT) which provides an octave-band analysis in the frequency domain, but might not be 'optimal' for a given signal. The discrete wavelet packet transform (DWPT) provides a dictionary of bases over which one can search for an optimal representation (without constraining the analysis to an octave-band one) for the signal at hand. However, it is well known that both the DWT and the DWPT are shift-varying. Also, when these transforms are extended to 2-D and higher dimensions using tensor products, they do not provide a geometrically oriented analysis. The dual-tree complex wavelet transform (DT-CWT), introduced by Kingsbury, is approximately shift-invariant and provides directional analysis in 2-D and higher dimensions. In this paper, a method to implement a dual-tree complex wavelet packet transform (DTCWPT), has been discussed. To find the best complex wavelet packet frame for a given signal, the author adapts the basis selection algorithm by Coifman and Wickerhauser, providing a solution to the basis selection problem for the DT-CWPT. Lastly, how to extend the 2-band DT-CWT to an M-band DT-CWT (provided that $M = 2b$) using the same method is shown.

OBJECTIVE OF THE WORK

The main difficulty in dealing with biomedical signals is the extreme variability of the signals and the necessity to operate on case by case basis. Also, one does not know what is the pertinent information and at which scale it is located. For example, it is frequently the deviation of some signal feature from the normal that is the most relevant information for diagnosis. As a result, the problems tend to be less well defined than those in engineering and the emphasis is more on designing robust method that work in most circumstances, rather than procedures that are optimal under very specific assumptions.

Another important aspect of biomedical signals is that the information of interest is often a combination of features that are well localized temporally or spatially and other that are more diffuse. This requires the use of analysis methods sufficiently versatile to handle events that can be at opposite extremes in terms of their time-frequency localization.
So, a robust method is to be designed which work in most circumstances rather than under very specific assumptions.
The objective of the work is the storage of the biomedical signal after compression and de-noising using wavelet transform.

METHODOLOGY



- Literature survey
- Simulation
- Designing of Algorithm
- Verification
- Publication of Papers
- Compilation of the results

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